Storyboarding OF RECIPES: GROUNDED CONTEXTUAL GENERATION

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ABSTRACT

Information need of humans is essentially multimodal in nature, enabling maximum exploitation of situated context. We introduce a dataset for sequential procedural (*how-to*) text generation from images in cooking domain. The dataset consists of 16,441 cooking recipes with 160,479 photos associated with different steps. We setup a baseline motivated by the best performing model in terms of human evaluation for the Visual Story Telling (ViST) task. In addition, we introduce two models to incorporate high level structure learnt by a Finite State Machine (FSM) in neural sequential generation process by: (1) Scaffolding Structure in Decoder (SSiD) (2) Scaffolding Structure in Loss (SSiL). These models show an improvement in empirical as well as human evaluation. Our best performing model (SSiL) achieves a METEOR score of 0.31, which is an improvement of 0.6 over the baseline model. We also conducted human evaluation of the generated grounded recipes, which reveal that 61% found that our proposed (SSiL) model is better than the baseline model in terms of overall recipes, and 72.5% preferred our model in terms of coherence and structure. We also discuss analysis of the output highlighting key important NLP issues for prospective directions.

1 INTRODUCTION

Interpretation is heavily conditioned on context. Real world interactions provide this context in multiple modalities. In this paper, the context is derived from vision and language. The description of a picture changes drastically when seen in a sequential narrative context. Formally, this task is defined as: given a sequence of images $\mathbb{I} = \{I_1, I_2, ..., I_n\}$ and pairwise associated textual descriptions, $\mathbb{T} = \{T_1, T_2, ..., T_n\}$; for a new sequence $\mathbb{I}^{'}$, our task is to generate the corresponding $\mathbb{T}^{'}$. Figure 1 depicts an example for making *vegetable lasagna*, where the input is the first row and the output is the second row. We call this a *'storyboard'*, since it unravels the most important steps of a procedure associated with corresponding natural language text. The sequential context differentiates this task from image captioning in isolation. The dataset is similar to that of ViST Huang et al. (2016) with an apparent difference between stories and instructional in-domain text which is the clear transition in phases of the narrative. This task supplements the task of ViST with richer context of goal oriented procedure (*how-to*). This paper attempts at capturing this high level structure present in procedural text and imposing it while generating sequential text from corresponding sequences of images.

Numerous online blogs and videos depict various categories of *how-to* guides for games, do-it-yourself (DIY) crafts, technology, gardening etc. This task lays initial foundations for full fledged storyboarding of a given video, by selecting the right junctions/clips to ground significant events and generate sequential textual descriptions. Although the main focus of this work is generating text from a given set of images. We are going to focus on the domain of cooking recipes in the rest of this paper, leaving the exploration of other domains to future. The two important dimensions to address in text generation are content and structure. In this paper, we discuss our approach in generating more structural/coherent cooking recipes by explicitly modeling the state transitions between different stages of cooking (phases). We introduce a framework to apply traditional FSMs to incorporate more structure in neural generation. We plan to explore backpropable variants in future. We acknowledge other backpropabale techniques to replace FSMs, which we leave for future work. We address the question of generating textual interpretation of the procedure depicted as a sequence of pictures (snapped at different instances of time as the procedure progresses).

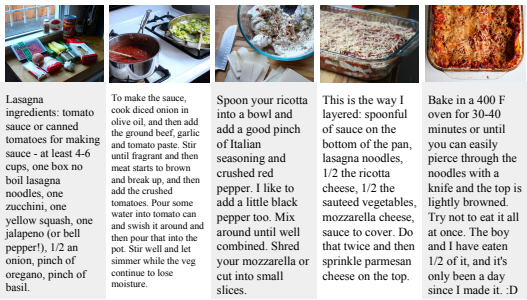


Figure 1: Storyboard for the recipe of vegetable lasagna

The two main contributions of this paper are: (1) a dataset of 16k recipes targeted for sequential multimodal procedural text generation (2) two models (SSiD: Structural Scaffolding in Decoder ,and SSiL: Structural Scaffolding in Loss) for incorporating high level structure learnt by an FSM into a neural text generation model to improve structure/coherence.

The rest of the paper is organized as follows. Section 2 describes the related work performed along the lines if planning while generating, understanding food and visual story telling. Section 3 describes the data we gathered for this task and related statistics. In Section 4, we clearly describe our models: a baseline model (Glocal), SSiD and SSiL. Section 5 presents the results attained from each of these models both empirically and qualitatively. Section 6 concludes this work and presents some future directions.

2 Related Work

Why domain constraint? Martin et al. (2017) and Khalifa et al. (2017) demonstrated that the predictive ability of a seq2seq model improves as the language corpus is reduced to a specialized domain with specific actions. Our choice of restricting domain to recipes is inspired from this, where the set of events are specialized (such as 'cut', 'mix', 'add') although we are not using event representations explicitly.

Planning while writing content: A major challenge faced by neural text generation Lu et al. (2018) while generating long sequences is the inability to maintain structure, contravening the coherence of the overall generated text. This aspect was also observed in various tasks like summarization Liu et al. (2018), story generation Fan et al. (2019). Pre-selecting content and planning to generate accordingly was explored by Puduppully et al. (2018) and Lukin et al. (2015) in contrast to generate as you proceed paradigm. Fan et al. (2018) adapt a hierarchical approach to generate a premise and then stories to improve coherence and fluency. Yao et al. (2018) experimented with static and dynamic schema to realize the entire storyline before generating. However, in this work we propose a hierarchical multi task approach to incorporate structure.

Comprehending Food: Recent times have seen large scale datasets in food, such as Recipe1M Marin et al. (2018), Food-101 Bossard et al. (2014) and bench-marking challenges like iFood challenge [1]. Food recognition Arora et al. (2019) addresses understanding food from a vision perspective. Salvador et al. (2018) worked on generating cooking instructions by inferring ingredients from an image. Zhou et al. (2018) proposed a method to generate procedure segments for YouCook2 data. In NLP domain, this is studied as generating procedural text by including ingredients as checklists Kiddon et al. (2016) or treating the recipe as a flow graph Mori et al. (2014). Our work is at the intersection of two modalities by generating procedural text for recipes from a sequence of images.

Visual Story Telling: Research at the intersection of language and vision is accelerating with tasks like image captioning Hossain et al. (2019), visual question answering Wu et al. (2017), visual dialog Das et al. (2017) , Mostafazadeh et al. (2017), de Vries et al. (2017), de Vries et al. (2018)). *ViST* Huang et al. (2016) is a sequential vision to language task demonstrating differences between descriptions in isolation and stories in sequences. Along similar lines, Gella et al. (2018) created

[1] `https://www.kaggle.com/c/ifood2018`

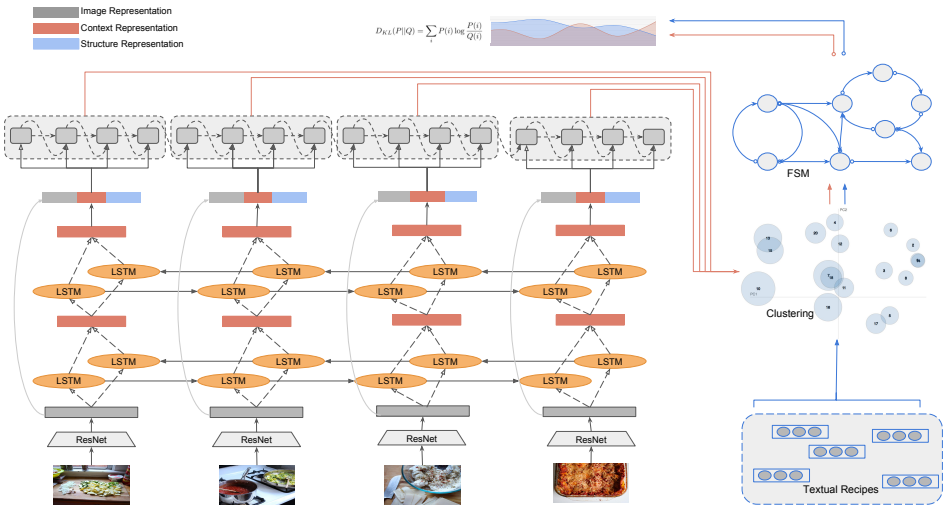


Figure 2: Architecture for incorporating high level structure in neural recipe generation

VideoStory dataset with videos posted on social media with the task of generating a multi-sentence story captions for them. Smilevski et al. (2018) proposed a late fusion based model for ViST challenge. Kim et al. (2018) attained the highest scores on human readability in this task by attending to both global and local contexts. We use this as our baseline model and propose two technique on top of this baseline to impose structure for procedural text.

3 Data Description

Food is one of the most photographed subject on the instagram network which led to coining the term *foodstagram*. We identified two *how-to* blogs: *instructables*[2] and *snapguide.com*[3], comprising step-wise instructions (images and text) of various *how-to* activities like games, crafts etc,. We gathered 16,441 samples with 160,479 photos [4] for food, dessert and recipe topics. We used 80% for training, 10% for validation and 10% for testing our models. In some cases, there are multiple images for the same step and we randomly select an image from the set of images. We indicate that there is a space for research here, while selecting most distinguishing or meaningful image. Details of the datasets are presented in Table 1. The distribution of the topics is visualized here[5]. A trivial extension could be done on other domains like fixing guitar strings etc, which is left for future work.

Data Sources	# Recipes	# Avg Steps
instructables	9,101	7.14
snapguide	7,340	13.01

Table 1: Details of dataset for *storyboarding* recipes

4 Model Description

We first describe a baseline model for this task here. We then propose two models with incremental improvements to address the structure of the generated recipes : SSiD (Scaffolding Structure in Decoder) and SSiL (Scaffolding Structure in Loss). The architecture of *scaffolding* structure is presented in Figure 2, of which different aspects are described in the following subsections.

[2] https://www.instructables.com/
[3] https://snapguide.com/
[4] ** *data will be released* **
[5] https://storyboarding.github.io/story-boarding/

4.1 BASELINE MODEL (GLOCAL):

We have a sequence of images at the different phases of cooking as our input and the task is to generate step wise textual descriptions of the recipe.

The baseline model is inspired from the best performing system in ViST challenge for human evaluation Kim et al. (2018). Image features for each step are extracted using ResNet-152 He et al. (2016). To maintain the context of the entire recipe (global context), these features are passed through a Bi-LSTM. To maintain specificity of the current image (local context), the image features are combined using a skip connection. These glocal vectors are used for decoding each step. LSTMs Gers et al. (1999) are trained with teacher forcing, applying batch normalization and dropout. The overall coherence in generation is addressed by feeding decoder state of the previous step is fed to the next one. This is a sequence to sequence model translating one modality into another. However, we know that procedural text has a high level structure that carries a skeleton of the text. The models described next impose this structure as a scaffold partially external to this baseline model and incorporating it in the decoder and in the loss terms.

4.2 SCAFFOLDING STRUCTURE IN DECODER (SSID):

There is a high level latent structure involved in a cooking recipe that adheres to transitions between steps, that we define as *phases*. Phases may be 'ingredients', 'baking', 'garnishing' etc., The key idea is to combine the phase sequences in the decoder to impose structure. There are two sources of supervision: (1) multimodal dataset $\mathbb{M} = \{\mathbb{I}, \mathbb{T}\}$ from Section 3, (2) unimodal textual recipes[6] $\mathbb{U}$ to learn phase sequences. Finer phases are learnt using clustering followed by an FSM.

Clustering: K-Means clustering is performed on the sentence embeddings with compositional n-gram features Pagliardini et al. (2018) on each step of the recipe in $\mathbb{U}$. Aligning with our intuition, when k is 3, it is observed that these clusters roughly indicate categories of *desserts*, *drinks* and *main course foods*, which comprise of *pizza*, *quesadilla* etc., However, we need to find out finer categories of the phases corresponding to the phases in the recipes. However, we need finer categories of phases. Hence, we experimented with different number of phases $\boldsymbol{P}$ as shown in Table 2. At this point, each recipe can be represented as a hard sequence of phases $\mathbf{r} = \langle\, p_1, p_2, p_3, p_4 \,\rangle$.

FSM: The phases learnt through clustering are not ground truth phases. We explore the usage of an FSM for a softer representation of the phase sequences by leveraging the states in an FSM. The algorithm was originally developed for building language models for limited token sets in grapheme to phoneme prediction. The iterative algorithm starts with an ergodic state for all phase types and uses entropy to find the best state split that would maximize the prediction. This is presented in algorithm 1. As opposed to phase sequences, each recipe is now represented as a state sequence (decoded from FSM) i.e, $\mathbf{r} = \langle s_1, s_2, s_3, s_4 \rangle$ (hard states). This is a hard representation of the state.

Since the phases are learnt in an unsupervised fashion and the ground truth of the phases is not available, we explored a softer representation of the states. We hypothesize that a soft representation of the states might smooth the irregularities of phases learnt. From the output of the FSM, we obtain the state transition probabilities from each state to every other state. Each state s_i can be represented as $\langle q_{ij} \; \forall \; j \in \boldsymbol{S} \rangle$ (soft states), where q_{ij} is the state transition probability from s_i to s_j and $\boldsymbol{S}$ is the total number of states. The structure in the recipe is learnt as a sequence of phases and state transition probabilities. This is the structural *scaffold* that we would like to incorporate in the baseline model. In SSiD model, for each step in the recipe, we identify which phase it is in using the clustering model and use the phase sequence to decode state transitions from the FSM. These state transition probabilities are concatenated in the decoder.

At this point, we have 2 dimensions, one is the complexity of the phases ($\boldsymbol{P}$) and the other is the complexity of the states in FSM ($\boldsymbol{S}$). Comprehensive results of searching this space is presented in Table 2. We plan to explore the usage of hidden markov model in place of FSM in future.

[6] www.ffts.com/recipes.htm

Algorithm 1 State Splitting in Weighted FSM (WFSM)

```
Result: FSM along with probabilistic state transitions
initialization while Until end criteria do
    Apply FSM to dataset;
    Record which phases in each recipe go through which states in the WFSM;
    For each state find entropy and reverse sort;
    for Each state in order do
        if if found an entropy reducing split then
            for Each each type coming into the state do
                calculate the entropy at each state if the existing one is split;
                The score is the each entropy times the number of examples going through that state ;
            end
        else
    end
    Once the best split is found, split moving all incoming arcs of that type to the new state (subtracting them from old one).
end
```

4.3 SCAFFOLDING STRUCTURE IN LOSS (SSIL):

In addition to imposing structure via SSiD, we explored measuring the deviation of the structure learnt through phase/state sequences from the original structure. This leads to our next model where we the deviation is reflected in the loss. The decoded steps are passed through the clustering model to get phase sequences and then state transition probabilities are decoded from FSM. We go a step further to investigate the divergence between the phases of generated and original steps. This can also be viewed as hierarchical multi-task learning Sanh et al. (2018). The first task is to decode each step in the recipe (which uses a cross entropy criterion, $\mathbf{L}_1$). The second task uses KL divergence between phase sequences of decoded and original steps to penalize the model (say, $\mathbf{L}_2$).When there are τ steps in a recipe, we obtain $o(s_1^\tau)$ and $g(s_1^\tau)$ as the distributions of phases comprising of soft states for the original and generated recipes respectively. We measure the KL divergence(D_{KL}) between these distributions:

$$D_{KL}(o(s_1^\tau)||g(s_1^\tau)) = \sum_{i=1}^{\tau}\sum_{j=1}^{S} o(s_i[j]) log \frac{o(s_i[j])}{g(s_i[j])}$$

Each task optimizes different functions and we minimize the combination of the two losses.

$$\sum_{I,T\in\mathbb{I},\mathbb{T}} \mathbf{L}_1(I,T) + \alpha \sum_{U\in\mathbb{U}} \mathbf{L}_2(U)$$

This combined loss is used to penalize the model. Here, α is obtained from KL annealing Bowman et al. (2015) function that gradually increases the weight of KL term from 0 to 1 during train time.

5 RESULTS AND DISCUSSION

The two dimensions explored in clustering and FSM are the number of phases that are learnt in unsupervised manner (***P***) and the number of states attained through state splitting algorithm in FSM (***S***). The results of searchng this space for best configuration are presented in Table 2.

FST Complexity	**1**	**20**	**40**	**60**	**80**	**100**	**120**
20 Phases	11.27	11.60	12.31	13.71	12.32	12.51	12.36
40 Phases	12.03	12.44	11.48	12.58	12.50	**13.91**	11.82
60 Phases	11.13	11.18	12.74	12.26	12.47	12.98	11.47

Table 2: BLEU Scores for different number of phases (***P***) and states(***S***)

The BLEU score Papineni et al. (2002) is the highest when ***P*** is 40 and ***S*** is 100. Fixing these values, we compare the models proposed in Table 3. The models with hard phases and hard states are not as stable as the one with soft phases since backprop affects the impact of the scaffolded phases. Upon manual inspection, a key observation is that for SSiD model, most of the recipes followed a similar structure. It seemed to be conditioned on a global structure learnt from all recipes rather than the

current input. However, SSiL model seems to generate recipe that is conditioned on the structure of that particular example.

Models	BLEU	METEOR	ROUGE-L
Glocal	10.74	0.25	0.31
SSiD (hard phases)	11.49	0.24	0.31
SSiD (hard states)	11.93	0.25	0.31
SSiD (soft states)	13.91	0.29	0.32
SSiL (soft states)	**16.38**	**0.31**	**0.34**

Table 3: Evaluation of storyboarding recipes

Human Evaluation: We have also performed human evaluation by conducting user preference study to compare the baseline with our best performing SSiL model. We randomly sampled generated outputs of 20 recipes and asked 10 users to answer two preferences: (1) overall recipe based on images, (2) structurally coherent recipe. For the second question, we gave examples of what structure and phases mean in a recipe. Our SSiL model was preferred 61% and 72.5% for overall and structural preferences respectively. This shows that while there is a viable space to improve structure, generating an edible recipe needs to be explored to improve the overall preference.

5.1 Qualitative Analysis:

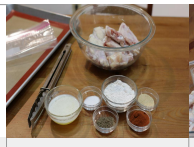
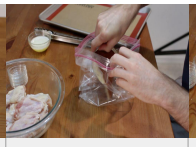
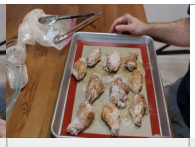
Models					*Phenomena*
Glocal Model	This is a simple recipe for making a delicious chicken salad.	You will need: a butter knife a plate of bread flour a little bit of salt a dash of pepper flakes a couple of tablespoons of olive oil a pinch of sugar.	Add butter evenly on the pan.	Put the chicken on the grill and set aside.	- Ingredients phase wrongly identified. - Wrong ingredients. - Improper conclusion.
SSiD Model	This is a simple recipe for making a delicious and easy dish.	Ingredients: 4 pounds chicken 2 tsp salt, ½ tsp sugar, marinara sauce, mozzarella cheese (i used provolone). Tools: a knife, an oven for the chicken, tongs. Mix all ingredients in a bag.	Add butter evenly on the pan.	Serve the baked chicken wings and enjoy the evening!	- Learnt majority structure (step 1) + Got 'tongs' right because of separate tools mention. - The action of baking is not explicitly mentioned (before 'baked' wings).
SSiL Model	You will need: 5 pounds of chicken wings, ½ cup all purpose flour, ½ tsp salt, 2 tsp of paprika, melted butter, silicon mat, baking pan.	Preheat oven to 450 F. Mix dry ingredients in the dry ziplock bag.	Place a mat on the baking pan and spread butter evenly on it.	Spread the chicken pieces on butter on the baking pan. Bake until crispy for 30 minutes. Serve and enjoy!	+ Global context of baking maintained in preheating. + Non-repetitive ingredients phase. + Referring expressions (baking pan -> it). - Not mentioned tools (tongs).

Figure 3: Comparison of generated *storyboards* for *Easy Oven Baked Crispy Chicken Wings*

Figure 3 presents the generated text from the three models with an analysis described below.

Coherence of Referring Expressions: Introducing referring expressions is a key aspect of coherence Dale (2006), as seen in the case of *'baking pan'* being referred as *'it'* in the SSiL model.

Context Maintenance: Maintaining the overall context explicitly has an effect in the generation of each step. This is reflected in SSiL model where *'preheating'* is discussed in second step although the image does not show an oven. This structure is learnt from *baking* step that appears later.

Schema for Procedural Text: Explicitly modeling structure for procedural text has enabled the model to conclude the recipe in SSiD and SSiL models by generating words like *'serve'* and *'enjoy'*. Lacking this structure, Glocal model talks about *setting aside* at the end of the recipe.

Precision of Entities and Actions: SSiD model introduces *'sugar'* in ingredients after generating *'salt'*. A brief manual examination revealed that this co-occurrence is a common phenomenon. Similarly *sauce* and *cheese* are wrongly generated. SSiL model misses *'tongs'* in the first step.

Parallels to Summarization: There is an inherent trade-off between detailing and presenting a concise overview. For instance, one might not need detailing on how onions are cut in comparison to how layering of cheese is executed. Although, we are not explicitly addressing the issue of

identifying complicated and trivial steps, a storyboard format implicitly takes care of this by briefing in pictorial representation and detailing in text. This draws parallels with multimodal summarization.

6 CONCLUSIONS

Our main focus in this paper is instilling structure learnt from FSMs in neural models for sequential procedural text generation with multimodal data. Recipes are being presented in the form of graphic novels reflecting the cultural change in expectations of presenting instructions. With this change, a storyboard is a comprehensive representation of the important events. In this direction, we gather a dataset of 16k recipes where each step has text and associated images. The main difference between the dataset of ViST and our dataset is that our dataset is targeted at procedural *how-to* kind of text (specifically presenting cooking recipes in this work). We setup a baseline inspired from the best performing model in ViST in the category of human evaluation. We learn a high level structure of the recipe as a sequence of phases and a sequence of hard and soft representations of states learnt from a finite state machine. We propose two techniques for incorporating structure learnt from this as a scaffold. The first model imposes structure on the decoder (SSiD) and the second model imposes structure on the loss function (SSiL) by modeling it as a hierarchical multi-task learning problem. We show that our proposed approach (SSiL) improves upon the baseline and achieves a METEOR score of 0.31, which is an improvement of 0.6 over the baseline model.

We plan on exploring backpropable variants as a scaffold for structure in future. We also plan to extend these models to other domains present in these sources of data. There is no standard way to explicitly evaluate the high level strcuture learnt in this task and we would like to explore evaluation strategies for the same.

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